ARTICLE IN PRESS

Transportation Research Part D xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

# Urban bus ridership, income, and extreme weather events

Nicole S. Ngo

*School of Planning, Public Policy and Management, University of Oregon, United States*

ARTICLE INFO

*Keywords:*
Extreme weather
Public transit
Bus ridership
Heat waves

ABSTRACT

Climate change is projected to worsen weather extremes, such as heat waves and days of heavy precipitation, which could pose serious health and economic risks to U.S. cities. These extreme weather events could also affect urban mobility, since people who walk or bike may shift to public transit or avoid travel if they cannot afford a vehicle. To address these concerns, this study examines the effects of extreme weather events on bus ridership and the extent to which this relationship varies by income and destination. This study analyzes highly detailed micro-level bus data between 2012 and 2017 for a county in the Pacific Northwest using a negative binomial regression model. Results suggest modest reductions in bus ridership on very hot and cold days, as well as on days with heavy rainfall, with impacts differing between weekdays and weekends. Findings also show that bus ridership is more sensitive to extreme weather events in lower-income areas relative to the wealthiest neighborhoods, which may be partly driven by a large university student population who can ride the bus for free. Finally, results show that bus ridership around commercial areas and parks increases on very cold days and days with heavy precipitation, reinforcing the importance of public transit during these weather events. These results suggest extreme weather events affect urban mobility, with greater impacts in lower-income neighborhoods, parks and commercial areas. Transit agencies and policymakers should consider ways to increase accessibility and mobility during these weather events, especially for lower-income households.

## 1. Introduction

Climate change is expected to worsen weather extremes, such as heat waves and heavier rainfall, which could pose serious health and economic risks to cities in the U.S. The most recent report from the U.S. Global Change Research Program's Fourth National Climate Assessment reinforces these concerns (Hayhoe et al., 2018). The report describes the last decade as the warmest on record and that average temperatures are expected to continue increasing. Another major concern with climate change includes dramatic changes in seasonal precipitation patterns, where heavy rainfall is expected to increase in frequency and intensity in many parts of the U.S. This is the case in regions like the Pacific Northwest, which includes Oregon, Washington, and Idaho, where models predict that heavy rainfall events and heat waves will increase, while cold waves are expected to decrease (May et al., 2018).

These extreme weather events could affect urban mobility, specifically travel mode or trip generation, if people who walk or bike shift to public transit or avoid travel (Sabir, 2011; Böcker et al., 2013). Numerous studies have examined the relationship between weather and urban mobility, though a literature review by Böcker et al. (2013) suggests that more studies have focused on biking and walking and less on public transit. And even fewer studies have considered the role of socioeconomic status or geographic characteristics on this relationship (Böcker et al., 2013; Sabir et al., 2013). Consequently, understanding how weather extremes influence travel behavior could help policymakers assess future plans for public transportation under climate change.

*E-mail address:* nngo@uoregon.edu.

https://doi.org/10.1016/j.trd.2019.03.009

1361-9209/ © 2019 Elsevier Ltd. All rights reserved.

Please cite this article as: Nicole S. Ngo, Transportation Research Part D, https://doi.org/10.1016/j.trd.2019.03.009

This study builds upon the existing literature and has three main objectives. First, it determines the effects of extreme weather events on bus ridership within Lane County, Oregon. Second, this study compares changes in bus ridership during extreme weather events by income across different neighborhoods. Heat waves or increased flood risk could particularly harm low-income households who have less resources to deal with these events, including a lower probability of affording alternative transportation modes. Third, this study observes if bus stops near commercial zones and municipal parks, areas associated with business and leisure, are affected more than other areas.

This study leverages a unique panel data set using micro-level bus data, exceeding 32 million observations, from the Lane Transit District (LTD), which serves Lane County, Oregon. These data include the number of people who alight and board at the bus stop-time-date level. Given the availability and accessibility of precipitation and temperature data, the extreme weather events of interest in this study are heat waves, cold waves, and high amounts of rainfall. A negative binomial regression model is used to assess these relationships. Given the high resolution of these data, ample control variables are also included and results are compared across different specifications to test for robustness.

Policymakers and transit agencies could use results from this study to improve our understanding of how climate change will affect public transit ridership. This includes considering the role of public transit as a complement or substitute to other travel modes, such as biking or walking, and transportation network companies, like Uber or Lyft. Additionally, if bus ridership in low-income neighborhoods or near commercial zones or municipal parks are more sensitive to extreme weather, then transit agencies and policymakers could consider ways to increase access to these areas during these weather events.

## 2. Background and literature review

While many studies have examined the effects of weather on biking and walking, fewer studies have focused on public transit, and results in the existing literature are mixed (Böcker et al., 2013). Some studies in this literature use travel survey data, but this study focuses on comparable work looking at the impacts of weather using public transit ridership data, which is a valid measure of ridership. A few studies find public transit ridership decreases with poor weather. A study by Tang and Thakuriah (2012) in Chicago and Hofmann and O'Mahony (2005) in Ireland find precipitation and snow are associated with decreases in bus ridership. One study by Kalkstein et al. (2009) finds that rail ridership increases on dry, comfortable days compared to more humid, cool weather in three U.S. metropolitan areas, including the Bay Area, Chicago, and northern New Jersey. Arana et al. (2014) examine impacts on transit buses in Gipuzkoa, Spain and find high wind and rain are associated with a reduction in trips, while higher temperatures are associated with an increase in trips.

However, other studies report more mixed results. Stover and McCormack (2012) find low temperatures and rain are associated with decreases in bus ridership in Pierce County, Washington, though effects varied by season. Guo et al. (2007) find bus and train ridership in Chicago decreases with rain and snow, though with heavy snow, train ridership increases. Singhal et al. (2014) find differential impacts of weather for daily and hourly subway ridership in New York City. A study by Sabir (2011) finds that more people switch from biking to public transport on days of rain, especially for leisure trips in the Netherlands. Another study by Sabir et al. (2013) find modal choice in the Netherlands depends on congestion due to weather and that income is associated with an increase in the likelihood of using the train for travel to the beach.

The range of results in this literature likely reflect differences in the climates and regions observed in these studies. Given the relatively mild climate of the Pacific Northwest, it may be difficult to compare this study to other work that occurred in areas that experience more humidity, wind, or snow. Additionally, some of these studies took place in large cities, where buses are more frequent and prevalent relative to many small- or medium-sized cities, which could also affect how sensitive bus ridership is to extreme weather events.

This study builds upon previous work, but differs in a few ways by addressing several shortcomings in the current literature. First, while some studies focus on smaller weather changes, other work shows large changes in temperature or precipitation could have very different impacts on public transit ridership (e.g., Guo et al., 2007). Consequently, the first objective of this study further explores the effects of extreme weather events on bus ridership in a medium-sized metropolitan area in the Pacific Northwest. Results from this study could offer more information on the effects of extreme weather on urban mobility in smaller U.S. cities.

The second objective contributes to the handful of studies that focus on the role of socioeconomic status (Böcker et al., 2013). For example, studies by Sabir (2011) and Sabir et al. (2013) are among the few studies that explicitly control for income in their analysis on travel mode and weather within this literature. This study builds upon their work by explicitly examining differences among lower- and higher-income populations. Low-income populations have limited access to alternatives, like private vehicles, forcing them to more heavily rely on the bus or not travel. As a result, they may be more sensitive to extreme weather compared to other populations, especially in smaller cities where buses are less frequent and waiting times outside are longer.

Finally, the third objective of this study investigates the importance of destination by exploring the effects on bus ridership at municipal parks and commercial zones during these extreme weather events. Impacts to or from these areas could reflect differences in leisure versus commuting trips. For example, Cools et al. (2010) find that trip purpose changes travel behavior in response to weather conditions in Flanders, Belgium. Also, studies suggest a relationship exists among temperatures and travel to parks. For example, a study by Scott et al. (2007) finds that more people may go to parks due to warmer temperatures. Analyzing the impacts of bus ridership to or from commercial zones or municipal parks could also provide more information about economic impacts in the long-run if extreme weather events continue to intensify.

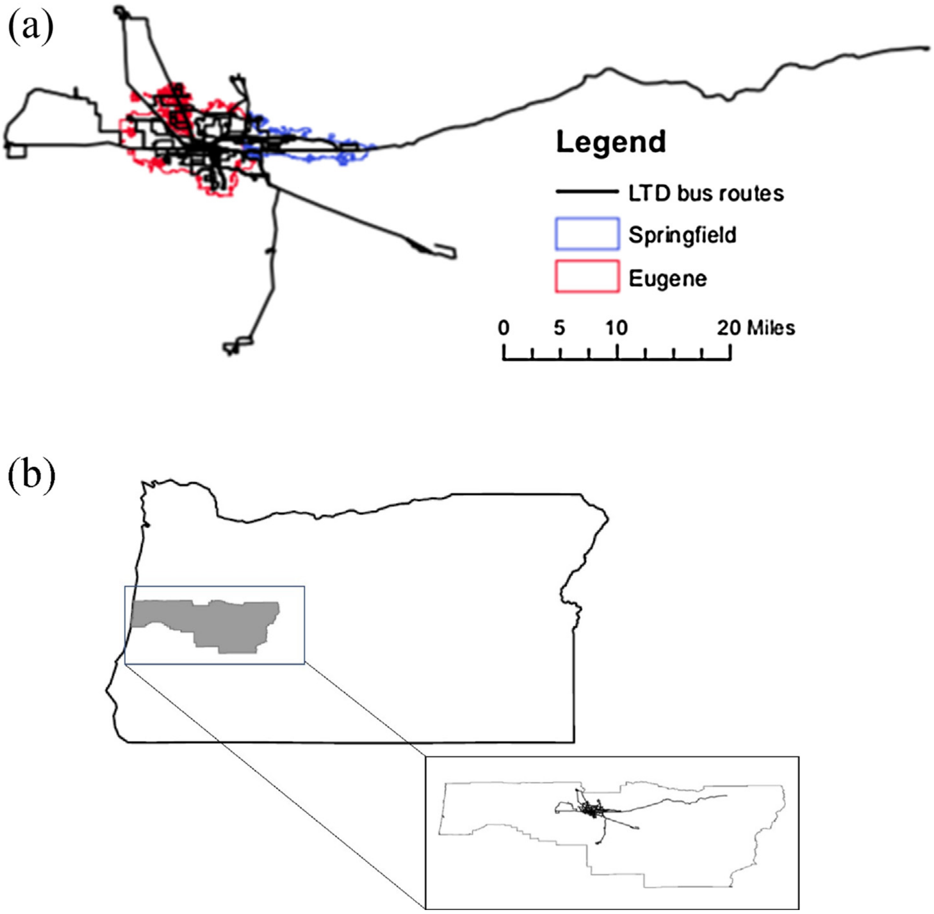


**Fig. 1.** (a) This figure shows the Lane Transit District (LTD) bus routes (black lines) and the city for Eugene (red) and Springfield (blue) in Lane County. Most of the bus routes are concentrated in these two cities, which are the largest cities in Lane County. LTD also operates in nearby cities including Coburg, Cottage Grove, Creswell, Dexter, Junction City, Lowell, McKenzie Bridge, Pleasant Hill, Veneta, Vida, and Walterville. (b). This figure shows the location of Lane County in Oregon (shaded in gray) and the inset shows the LTD bus routes in Lane County. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

## 3. Setting and data

### *3.1. Lane County and the Lane Transit District (LTD)*

Oregon, like other parts of the U.S. Pacific Northwest, is characterized as having a Mediterranean climate, with wet winters and warm, dry summers. Its climate is relatively mild compared to other U.S. regions. However, by the end of the century, climate models predict that heat waves and heavy precipitation in this region will increase, like in many other regions of the U.S. (Hayhoe et al., 2018).

This study takes place in the Pacific Northwest, specifically Lane County, Oregon. Lane County has a population of 360,000 people and is the fourth largest county in Oregon. The largest city in Lane County is Eugene with a population of 166,000, and the second largest is the adjacent city of Springfield with a population of 62,000 (U.S. Census Bureau, 2018). Eugene is also a college town home to the University of Oregon, a large public university with nearly 27,000 students (University of Oregon, 2018). There is also a strong rural presence outside the Eugene-Springfield area, where population density is dramatically lower.

The public transit system in Lane County is represented by LTD, which started in 1970 and has continued to expand its services since then (LTD, 2018a). Fig. 1 shows a map of LTD bus routes, which are clustered around Eugene and Springfield and nearby towns, including Coburg, Cottage Grove, Creswell, Dexter, Junction City, Lowell, McKenzie Bridge, Pleasant Hill, Veneta, Vida, and Walterville. The LTD is responsible for over 1500 bus stops and 62 bus routes. Fares for a single ride for adults is $1.75 and is free for those who are older than 65 and children under 5 (LTD, 2018b). Older children between the ages of 6 and 18 or people with disabilities pay half the fare ($0.85). Enrolled students and employees of the University of Oregon ride the bus for free. Most buses run every hour or half hour depending on the bus stop, season, and time, so they are less frequent compared to bus or rail systems in larger metropolitan areas.

ARTICLE IN PRESS



**Table 1**
Summary statistics for the independent variables of interest and dependent variable in Lane County (2012–2017).

| | N | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|---|
| Daily total ridership | 2,267,001 | 56 | 264 | 0 | 9205 |
| Daily maximum temperature (˚F) | 2,267,001 | 65 | 16 | 29 | 105 |
| Daily precipitation (in.) | 2,267,001 | 0.13 | 0.28 | 0 | 5 |
| Annual household income per census tract (US$) | 2,267,001 | 56,454 | 18,875 | 15,008 | 115,009 |

Notes: This table shows summary statistics for the dependent variable, total bus ridership, which is the sum of those who aboard and alight at a given Lane Transit District (LTD) bus stop and date between 2012 and 2017 for the months of January to December. Data for daily maximum temperature and total precipitation are from the National Centers for Environmental Information. Data for annual mean household income data at the census-tract level are from the 2016 5-year American Community Survey.

### 3.2. Dependent variable: Bus ridership

The LTD buses are equipped with automatic passenger counters, which record the number of people who board and alight each time the bus stops at an LTD stop. These bus data were obtained from LTD through a public records request for the period between January and December for the years of 2012 to 2017. During the study period, there were no major changes to bus routes or stops. For this analysis, the dependent variable is bus ridership, which is defined as the total number of people who alight and board at a given LTD bus stop. These panel data include more than 32 million observations, which covers the universe of trips in Lane County for the study period. Since this study is focused on impacts during average daily travel, observations that fall outside the normal bus schedule are dropped, specifically observations after 11 pm and before 5 am, which represent only 0.5% of the total data set. These data are then aggregated up to the daily level to observe impacts on average daily ridership. A GIS map of LTD bus routes is also obtained (Fig. 1). Table 1 shows summary statistics, where average daily bus ridership is 56 people and the standard deviation is 264 people. The very high standard deviation suggests overdispersion may be a problem.

### 3.3. Independent variables of interest

#### 3.3.1. Weather variables

Information on average daily maximum temperatures and precipitation is gathered across weather stations at the city-level in Lane County from the National Centers for Environmental Information.[1] Table S1 in the supplementary information shows the list of weather stations used in this analysis.[2] Daily maximum temperature is used since it better reflects worsening heat waves, which are expected to increase in the Pacific Northwest while cold waves will likely decrease (Hayhoe et al., 2018). In the main specification, categorical variables are used to capture the relationship between extreme weather events and bus ridership. Variation in climate and region influences how individuals define "extreme weather events." As a result, for daily maximum temperature, thresholds are approximated around the 10th and 90th percentiles, since they represent colder or hotter than usual weather.[3] The 10th and 90th percentile for daily maximum temperature in Lane County during the study period is 46 ˚F and 86 ˚F (resp.). To also ensure the range within each temperature category is relatively similar, maximum temperatures below 50 ˚F or greater than or equal to 85 ˚F are considered "very cold" or "very hot" (resp.). The independent variables of interest for temperature in the main specification are three different dummy variables which equal 1 when daily maximum temperature is less 50 ˚F, between 50 and 70 ˚F, and greater than or equal to 85 ˚F and 0 otherwise. The reference category represents daily maximum temperatures between a more comfortable 70 and 85 ˚F.

For daily precipitation, the 10th and 90th percentile is 0 and 0.43 in. (resp.). Thresholds for categorical variables are determined around extremely high rainfall events, and are approximated around the 90th percentile for precipitation and 1 in., which represents downpours or extremely heavy precipitation according to other studies (e.g., Mote et al., 2014). Consequently, the independent variables of interest representing precipitation in the main specification are two dummy variables equal to 1 if precipitation is between 0.5 in. and 1 in. or greater than 1 in. and 0 otherwise. The reference category is less than 0.5 in.

While this study is limited to one particular region of the country, given the range of climates in the U.S. and the world, it is important to observe the effects of extreme weather in all types of settings. One possible criticism of this work is that this study does not account for relative humidity and wind speed. Unfortunately, these data are not consistently available, so the sample size would have reduced dramatically by including them. However, this is not a major concern because the climate in the Pacific Northwest is

[1] Since there are no GIS maps of city boundaries across all cities in Lane County, cities are determined by zip codes which are all associated with a city. It is not unusual for zip codes to extend beyond official city boundaries (e.g., Fig. S1 in the supplementary information). However, this is not a major concern since weather should not differ dramatically among cities in close proximity to each other and at a similar altitude.

[2] In instances where more than one weather station is present in a given city (e.g., Cottage Grove), then the average is taken across all weather stations in that city for daily maximum temperature and precipitation.

[3] Other cities in close proximity to Eugene also had weather data, specifically Veneta and Lowell, but these data were not as consistent, so Eugene data were used to represent bus stops in these cities. Additionally, the National Centers for Environmental Information did not have weather data for the following cities in Lane County: Dexter, Creswell, Coburg, Junction City, and Pleasant Hill. For these cites, weather data for Eugene were also used.

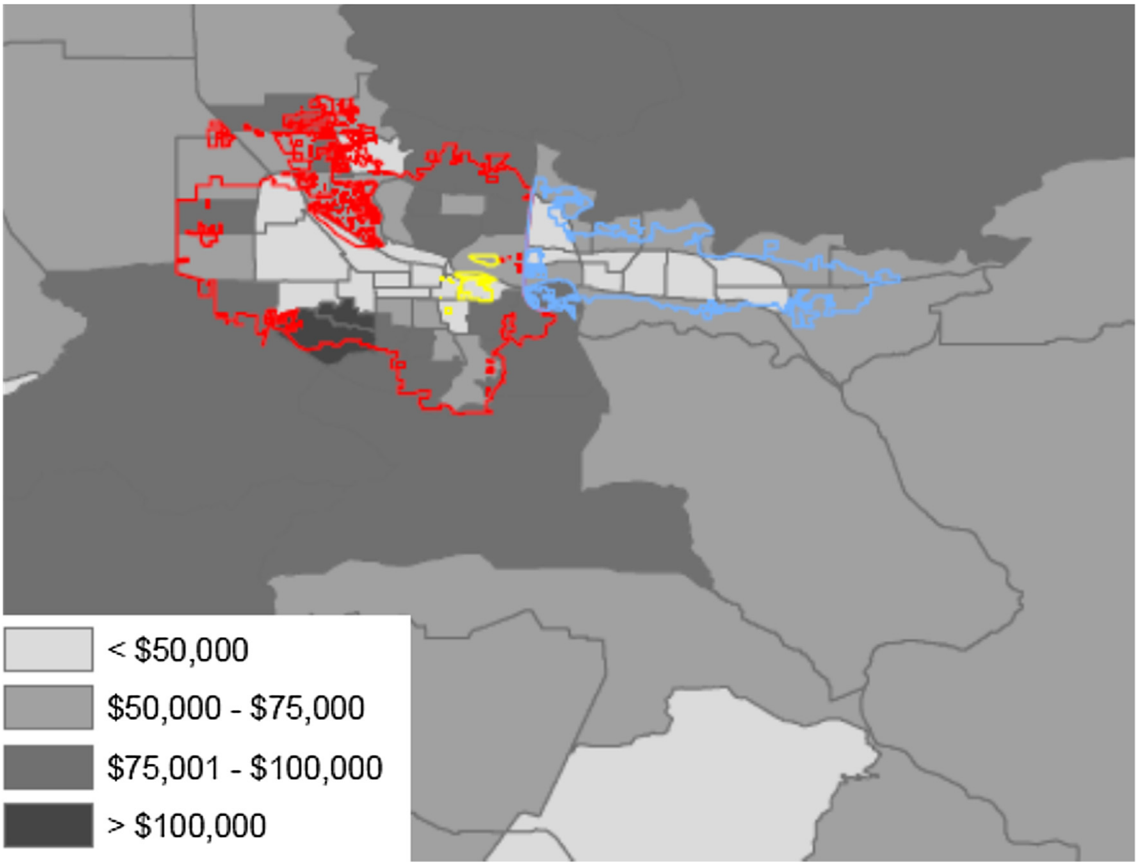


**Fig. 2.** This map shows mean annual household income using the 2016 5-year American Community Survey. The red and blue outlines represent the official boundaries of Eugene and Springfield (resp.) and the yellow outline shows the University of Oregon, where a large student population tends to reside. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

characterized as mild, with warm, dry summers and wet winters, relative to other U.S. regions, so humidity and wind are not major factors. Yet, in regions with more severe weather, humidity, wind or snow, could be important to consider. This reinforces the importance of examining regions around the U.S., as well as in cities of different sizes since impacts could be greater in small- or medium-sized cities where public transit is less frequent and waiting times are longer.

#### *3.3.2. Income, commercial zones, and municipal parks*

To observe how individuals of different income levels respond to using the bus during extreme weather events, information on mean annual household income at the census tract level is collected from the 2016 5-year American Community Survey (ACS). A GIS map of 2010 U.S. census tracts is also used to map mean annual income for the 75 census tracts where LTD operates (Fig. 2). Eugene and Springfield are outlined in red and blue (resp.). Near the University of Oregon, which is outlined in yellow, incomes are less than $50,000. This partly reflects the large student population surrounding the university who can ride the bus for free. To put these incomes in perspective, the mean household income for Eugene and Springfield was $64,173 and $49,638 (resp.) in 2016, which both fall below the U.S. mean income of $77,866 (U.S. Census Bureau, 2018). Higher income households where mean annual income is greater than $50,000 are located in neighborhoods further away from the university. Outside the Eugene-Springfield area, where population is less dense, incomes are more diverse, reflecting the urban-rural divide in Lane County. Since the official threshold for “low-income” households varies by city, this work focuses on areas where annual mean household income is below $50,000 or “lower-income” areas.

Finally, a GIS map of municipal parks and commercial zones in Eugene and Springfield, the two largest cities in Lane County, is obtained from the University of Oregon library (Fig. 3) to assess the effects of bus ridership at these locations.[4]

[4] “Commercial zones” were determined using a zoning GIS map for Eugene and Springfield. It includes areas designated as neighborhood commercial zones, community commercial zones, major commercial zones, general office zones, and special commercial zones. The locations of municipal parks were determined based on a GIS map of Lane County municipal parks.

ARTICLE IN PRESS



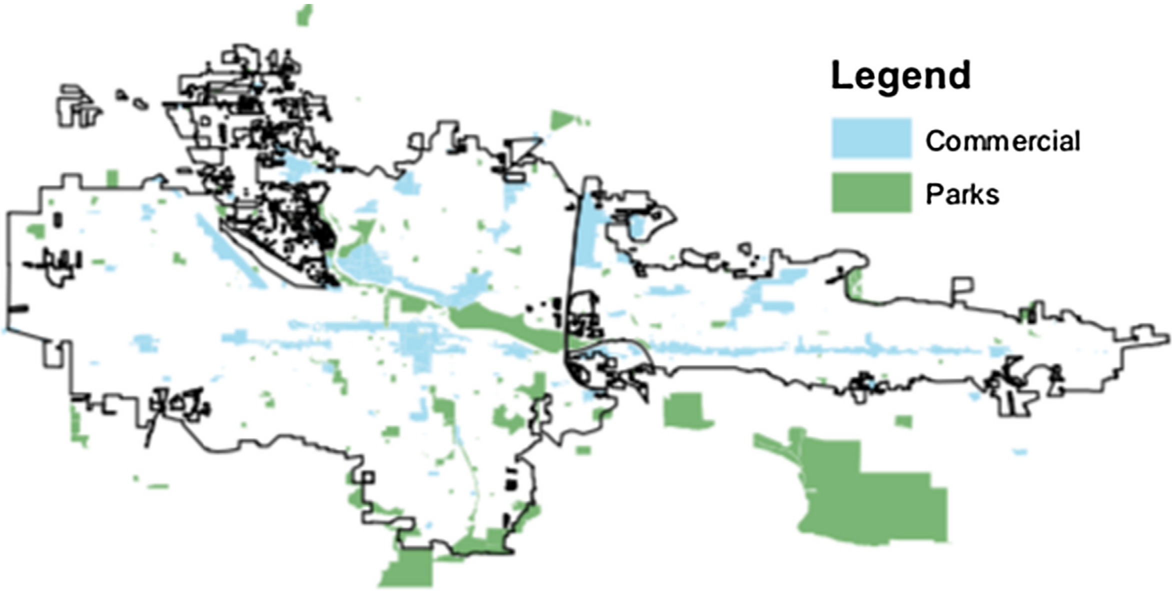


**Fig. 3.** This figure shows Lane County municipal parks (green) and commercial zones (blue) in Eugene and Springfield. The black lines show the official city boundaries of both cities. Zoning GIS maps for Eugene and Springfield are used and include neighborhood, community, major and office commercial zones. Also included are the Chambers special/community commercial zone in Springfield, as well as the Glenwood commercial and office mixed use zone in Springfield. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

### *3.4. Control variables*

To minimize omitted variable bias and reduce standard errors, several other covariates are included in this regression analysis. This includes dummy variables for each season, day-of-week, day-of-year, and month-year. A dummy variable equal to 1 if it is a major U.S. federal holiday and 0 otherwise is also included.[5] This accounts for temporal trends in bus ridership, including changes in LTD bus schedules between the summer and winter seasons. A linear date trend, which equals one on the first day of the study period, is also controlled for. Interaction terms between a dummy variable for each city and a continuous year variable are also included to account for linear annual trends for each city, like population, which could affect bus ridership. Finally, a dummy variable for each bus stop is also included to account for time-invariant characteristics at the bus stop level, such as traffic or type of bus stop.

## 4. Statistical analysis

### *4.1. Extreme weather events and bus ridership*

This study investigates the effects of extreme weather events on bus ridership, the first objective of this study, using categorical variables to represent different maximum temperatures and precipitation based on percentiles for each variable. This allows for more flexibility within temperature categories as opposed to assuming a linear relationship. Due to overdispersion, where the standard deviation exceeds the mean, in bus ridership and because bus ridership is a non-negative count variable, a negative binomial regression model is used. The following regression is the main specification:

$$\begin{aligned} ridership_{sct} = {} & \beta_0 + \beta_1(temp < 50)_{ct} + \beta_2(50 \leq temp < 70)_{ct} + \beta_3(temp \geq 85)_{ct} + \beta_4(0.5 \leq prcp < 1)_{ct} + \beta_5(prcp \geq 1)_{ct} + dow_t \\ & + month\_year_t + holiday_t + doy_t + date_t + city * year_{ct} + stop_s + \varepsilon_{sct} \end{aligned} \tag{1}$$

where *ridership* represents the total number of people who alight or board at bus stop *s* in city *c* on date *t*. The independent variables of interest for temperature are the dummy variables, $(temp < 50)$, $(50 \leq temp < 70)$, and $(temp \geq 85)$, which equal 1 when daily maximum temperature is less than 50 °F, between 50 and 70 °F, and greater than or equal to 85 °F (resp.) on date *t* in city *c*. The coefficients of interest for temperature are $\beta_1$, $\beta_2$, and $\beta_3$, which represent the effect on bus ridership when daily maximum temperature falls within one of these categories relative to more mild temperatures, represented by the reference category where daily maximum temperature is between 70 and 85 °F. For precipitation, the independent variables of interest are dummy variables equal to 1 if precipitation is between 0.5 in. and 1 in. $(0.5 \leq prcp < 1)$ or at least 1 in. $(prcp \geq 1)$. The coefficients of interest are $\beta_4$ and $\beta_5$,

[5] Major U.S. federal holidays include New Year's Day, Martin Luther King Jr. Day, Memorial Day, Independence Day, Labor Day, Columbus Day, Labor Day, Veteran's Day, Thanksgiving, the day after Thanksgiving, and Christmas.

which represent the effect of heavy rainfall events on bus ridership relative to days when precipitation is less than 0.5 in.

Control variables include dummy variables for each season (*season*), day-of-year (*doy*), day-of-week (*dow*) and month-year (*month_year*). The dummy variable, *holiday,* is also included and equal to 1 if it is a holiday and 0 otherwise. The variable, *city * year,* accounts for factors that trend annually for each city and *stop* represents a dummy variable for each bus stop. Linear date trends are also accounted for in the variable, *date*. Standard errors are estimated using the observed information matrix.

The impacts of extreme weather events may vary by weekends versus weekdays, so an alternative specification is considered which takes this into account. A modified version of Eq. (1) is used that includes an interaction term between a weekend dummy variable, which is equal to 1 if it is the weekend and 0 otherwise, and each temperature category represented in Eq. (1). A dummy variable for the weekend is also included. The coefficients on the interaction terms represent the change in bus ridership on weekends for a given temperature category relative to weekdays with more comfortable temperatures. This could possibly inform previous work examining how this relationship varies by trip type (i.e., leisure or commuting) (Sabir, 2011).

### 4.2. Extreme weather events, bus ridership, and income

Next, this study addresses the second objective of this study and examines how socioeconomic status, measured by income at the census tract level, influences bus ridership during these extreme weather events. Eq. (1) is expanded and includes interactions between different income categories and each temperature and precipitation category. The average annual income categories are income $<$ \$50,000, \$50,000 $\leq$ income $<$ \$75,000, and income $\geq$ \$75,000. The coefficients of interest are on these interaction terms and represent the change in bus ridership in a given income and maximum temperature or precipitation category relative to the reference category. The reference category is represented by census tracts where mean annual household income is greater than \$75,000 and days when daily maximum temperatures are between 70 and 85 °F or precipitation is less than 0.5 in.[6] Lower-income families, or those that make less than \$50,000, are expected to be more sensitive to extreme heat or cold and heavy precipitation relative to higher-income families because they are less likely to have access to alternative transportation, like a private vehicle.

### 4.3. Extreme weather events, bus ridership, municipal parks, and commercial zones

The third objective of this study examines the effects of extreme weather events on bus ridership at municipal parks in Lane County and commercial zones in Eugene and Springfield, the largest cities in Lane County and the only cities with zoning information, since trip purpose or type could affect this relationship (Fig. 3). Individuals may travel less or change travel modes if the weather is very hot or cold since studies show leisure trips are more sensitive to weather (e.g., Sabir, 2011). While trip purpose is not explicitly accounted for, especially since commercial zones are used for both leisure and business purposes, understanding travel around commercial zones or parks could have meaningful economic and recreational implications.

Eq. (1) is used, but also includes an interaction term between a dummy variable equal to 1 if the bus stop is located within 0.25 miles of a municipal park or commercial zone and is 0 otherwise, and a dummy variable for each temperature category. Dummy variables for parks and commercial zones are not included since they represent time-invariant characteristics that are captured in the dummy variables for bus stops. The coefficients on the interaction terms represent the change in bus ridership at bus stops near commercial zones in Eugene and Springfield or municipal parks in Lane County relative to bus stops not within 0.25 miles of these areas and to milder temperatures.[7] The same exercise is performed for precipitation in a separate regression.

## 5. Results

### 5.1. Extreme weather events and bus ridership

Results examining the effects of extreme weather events and bus ridership are in Table 2, where each column represents a separate regression. Coefficients are statistically significant if $p < 0.05$. Results using Eq. (1) are in column 1 and show that relative to the reference category of milder temperatures, bus ridership experiences a statistically significant decrease of 1.4% ($p < 0.01$) and 0.3% ($p < 0.05$) per bus stop and date when daily maximum temperature is less than 50 °F and above or equal to 85 °F (resp.). There are no significant effects on days when daily maximum temperature is between 50 and 70 °F. Findings also show a reduction of 3.3% ($p < 0.01$) and 5.1% ($p < 0.01$) when precipitation is between 0.5 and 1 in. and greater than 1 in. (resp.) relative to when precipitation is less than 0.5 in.

Results in column 1 do not account for possible differences between weekdays and weekends, though there may be heterogenous effects within weeks. Consequently, results in column 2 are from Eq. (1), but also include interaction terms between a dummy

[6] Since data from the 2016 5-year ACS is used, income is not included because it is a time-invariant characteristic in the main specification that is already captured by a dummy variable for each bus stop.

[7] Due to data constraints, this study cannot observe impacts across all commercial zones in Lane County. Instead it only focuses on impacts near commercial zones in Eugene and Springfield, using all other LTD bus stops as the control group. While this does not account for commercial zones in other cities in Lane County, this is not a major concern since Springfield and Eugene are the largest cities in Lane County, while the surrounding towns are dramatically smaller. As a result, commercial zones in these smaller towns are not comparable to the size or popularity of more traditional commercial areas in metropolitan areas, like Eugene and Springfield.

ARTICLE IN PRESS



**Table 2**
The effects of precipitation and maximum temperature on bus ridership using the main specification (Eq. (1)).

| | 1<br>Board and alight | 2<br>Board and alight |
|---|---|---|
| Maximum temperature < 50 °F | −0.014** | −0.0061** |
| | [0.0015] | [0.0016] |
| 50 °F ≤ Maximum temp < 70 °F | −0.0031** | 0.011** |
| | [0.0011] | [0.0011] |
| Maximum temp ≥ 85 °F | −0.0027* | −0.022** |
| | [0.0013] | [0.0014] |
| 0.5 in < Precipitation < 1 in | −0.033** | −0.038** |
| | [0.0013] | [0.0014] |
| Precipitation ≥ 1 in | −0.051** | −0.055** |
| | [0.0020] | [0.0021] |
| Weekend*(Maximum temperature < 50 °F) | | −0.057** |
| | | [0.0027] |
| Weekend*(50 °F < Maximum temp < 70 °F) | | −0.10** |
| | | [0.0022] |
| Weekend*(Maximum temp ≥ 85 °F) | | 0.11** |
| | | [0.0030] |
| Weekend*(0.5 in < Precipitation < 1 in) | | 0.034** |
| | | [0.0036] |
| Weekend*(Precipitation > 1 in) | | 0.030** |
| | | [0.0057] |
| N | 2,266,997 | 2,266,997 |

Notes: $^{**}p < 0.01$, $^{*}p < 0.05$. There are 1500 bus stops included in this analysis. Coefficients on the control variables for columns 1 and 2 are in columns 1 and 2 (resp.) in Table S1 in the supplementary information. See Section 4.1 for more information.

variable for the weekend and temperature or precipitation categories. The coefficient on the interaction term for very cold days in column 2 shows that weekend bus ridership decreases by 5.7% ($p < 0.01$) relative to weekdays. In row 1, column 2, which shows the change in bus ridership on very cold weekdays, bus ridership decreases by 0.6% ($p < 0.01$). On very hot weekends, bus ridership increases by 1.1% ($p < 0.01$) relative to weekdays, though bus ridership on very hot weekdays decreases by 2.2% ($p < 0.01$). This implies a smaller reduction in bus ridership on very hot weekends compared to weekdays. A similar pattern is shown on days with heavy precipitation, where changes in bus ridership on weekends are statistically significant and positive compared to weekdays, suggesting a smaller decrease in bus ridership on weekends. Coefficients on control variables for these results are in columns 1 and 2 of Table S2 in the supplementary information.

### 5.2. The role of income

Table 3 shows results using Eq. (1) and interacting different income levels with daily maximum temperature and precipitation categories. Due to space constraints, only results during very cold days, very hot days, and during heavy rainfall events are shown. Coefficients on days with more mild temperature and on control variables are in column 3 of Table S1 in the supplementary information. Findings show that bus ridership in lower-income areas, where average annual income is $50,000 or less, decreases by 1.6% ($p < 0.01$) on very hot days relative to wealthier tracts where income is ≥ $75,000. There is no significant effect on very cold days. On days with heavy precipitation, bus ridership in lower-income tracts increases by 1.9–2.7% ($p < 0.01$) relative to the highest-income tracts. In areas where average income is between $50,000 and $75,000, bus ridership decreases by 2.2% ($p < 0.01$) and 1% ($p < 0.01$) on very cold and hot days (resp.) relative to the wealthiest neighborhoods. While on days when precipitation exceeds 1 in., bus ridership increases by 2.2% ($p < 0.05$).

### 5.3. Impacts in municipal parks and commercial zones

Next, this study examines if bus ridership to or from commercial zones in Eugene and Springfield and municipal parks in Lane County changes during extreme weather events. Due to space limitations, only results on very hot days, very cold days, and days with heavy rainfall are shown. Results are in Table 4 and the coefficients of interest are on the interaction terms. Relative to control bus stops, results show statistically significant increases in bus ridership to parks and commercial areas on very cold days of 2.8% ($p < 0.01$) and 2% ($p < 0.01$) (resp.) relative to more mild weather in control areas. However, there is no statistically significant effect on very hot days to parks or commercial zones. Results also suggest show modest increases in bus ridership to parks and commercial areas of 0.8% ($p < 0.01$) and 1.1% ($p < 0.01$) (resp.) when precipitation is between 0.5 in. and 1 in. Finally, when precipitation exceeds 1 in., there is a statistically significant increase in bus ridership of 1.9% ($p < 0.01$), but no statistically significant effect in commercial zones. Results for the remaining independent variables are in column 4 of Table S1 in the supplementary information.

**Table 3**
The effects of extreme weather on bus ridership around census tracts with different mean annual income levels.

| | 1<br>Board and alight |
|---|---|
| Maximum temperature < 50 °F | −0.0068** |
| | [0.0027] |
| 50 °F ≤ Maximum temp < 70 °F | 0.012** |
| | [0.0020] |
| Maximum temp ≥ 85 °F | 0.0090** |
| | [0.0027] |
| 0.5 in ≤ Precipitation < 1 in | −0.045** |
| | [0.0036] |
| Precipitation ≥ 1 in | −0.073** |
| | [0.0056] |
| (Income < $50 K)*(Maximum temperature < 50 °F) | −0.000095 |
| | [0.0026] |
| (Income < $50 K)*(Maximum temp ≥ 85 °F) | −0.016** |
| | [0.0029] |
| (Income < $50 K)*(0.5 in ≤ Precipitation < 1 in) | 0.019** |
| | [0.0039] |
| (Income < $50 K)*(Precipitation ≥ 1 in) | 0.027** |
| | [0.0061] |
| ($50 K ≤ Income < $75 K)*(Maximum temperature < 50 °F) | −0.022** |
| | [0.0028] |
| ($50 K < Income < $75 K)*(Maximum temp ≥ 85 °F) | −0.0098** |
| | [0.0031] |
| ($50 K < Income < $75 K)*(0.5 in ≤ Precipitation < 1 in) | 0.0042 |
| | [0.0041] |
| ($50 K < Income < $75 K)*(Precipitation ≥ 1 in) | 0.022** |
| | [0.0064] |
| N | 2,266,997 |

Notes: **$p < 0.01$, *$p < 0.05$. Results are from using Eq. (1) and including interaction terms between different precipitation and temperature categories and annual mean income. Income data are from the 2015 5-year American Community Survey. See Section 4.2 for more information.

### 5.4. Robustness checks

A couple robustness checks are performed to test the sensitivity of results to different specifications and ensure results are not due to statistical chance. Robustness checks will focus on using Eq. (1) and findings in Table 2 to assess the appropriateness of using maximum temperature, as opposed to other measures of temperature, test different thresholds for temperature and precipitation categorical variables, and assess impacts within season.

#### 5.4.1. Average daily temperature

As a robustness check, average temperature instead of maximum temperature is used to assess the effects on bus ridership across different measurements of temperature. The average temperature is calculated by taking the mean of the daily minimum and maximum temperatures. Similar to ascertaining temperature categories for maximum temperature, categorical variables for average temperature are based on percentiles. The 10th and 90th percentiles for average temperature are 38 °F and 67 °F (resp.) and represent unusually cold or high temperatures (resp.). As a result, the categorical variable for average temperature are approximated around these percentiles and are represented by daily average temperature < 40 °F, 40 °F ≤ average temperature < 55 °F, and average temperature ≥ 70 °F. Each of these categories are represented by a dummy variable equal to 1 if daily average temperature falls within the appropriate range and is 0 otherwise. Eq. (1) is used, but the dummy variables for maximum temperature are replaced by these new dummy variables for average temperature, where the reference category is 55 °F ≤ average temperature < 70 °F. Results from this regression should be qualitatively similar to those in Table 2. Findings are in the supplementary information Table S3 and show a similar pattern as in Table 2, where bus ridership decreases during very cold weather (average temperature < 40 °F) and very hot weather (average temperature ≥ 70 °F) by 1.9% ($p < 0.01$) and 1.5% ($p < 0.01$) (resp.) relative to more comfortable temperatures.

#### 5.4.2. Different temperature and precipitation thresholds

As another robustness check to determine if temperature and precipitation thresholds used in Eq. (1) are appropriate, smaller temperature and precipitation bins are used. Specifically, the new categorical variables are daily maximum temperature < 40 °F, 40 °F ≤ maximum temperature < 50 °F, 50 °F ≤ maximum temperature < 60 °F, 80 °F ≤ maximum temperature < 90 °F, and maximum temperature ≥ 90 °F and these replace the temperature categories in Eq. (1). The reference category is represented by more mild daily maximum temperatures between 60 and 80 °F. The new categories for precipitation are

**Table 4**
The effects of extreme weather events on bus ridership around parks or commercial zones.

| | 1<br>Board and alight |
|---|---|
| Maximum temperature $< 50$ °F | $-0.041^{**}$ |
| | [0.0022] |
| 50 °F ≤ Maximum temp $< 70$ °F | $-0.016^{**}$ |
| | [0.0017] |
| Maximum temp ≥ 85 °F | −0.0042 |
| | [0.0023] |
| 0.5 in $<$ Precipitation $<$ 1 in | $-0.045^{**}$ |
| | [0.0026] |
| Precipitation ≥ 1 in | $-0.063^{**}$ |
| | [0.0040] |
| Parks*(Maximum temperature $< 50$ °F) | $0.028^{**}$ |
| | [0.0019] |
| Parks*(Maximum temp ≥ 85 °F) | −0.0013 |
| | [0.0021] |
| Parks*(0.5 in ≤ Precipitation $<$ 1 in) | $0.0083^{**}$ |
| | [0.0025] |
| Parks*(Precipitation ≥ 1 in) | $0.019^{**}$ |
| | [0.0038] |
| Commercial zones*(Maximum temperature $< 50$ °F) | $0.020^{**}$ |
| | [0.0022] |
| Commercial zones*(Maximum temp ≥ 85 °F) | 0.0032 |
| | [0.0024] |
| Commercial zones*(0.5 in ≤ Precipitation $<$ 1 in) | $0.011^{**}$ |
| | [0.0029] |
| Commercial zones*(Precipitation ≥ 1 in) | 0.0068 |
| | [0.0044] |
| N | 2,266,997 |

Notes: $^{**}p < 0.01$, $^{*}p < 0.05$. This analysis focuses on Eugene and Springfield only. There are 1180 bus stops within the Springfield and Eugene city boundaries. See Section 4.3 for more information.

0.25 in. ≤ precipitation $<$ 0.5 in., 0.5 in. ≤ precipitation $<$ 0.75 in., 0.75 in. ≤ precipitation $<$ 1 in., precipitation ≥ 1 in. The reference category is precipitation $<$ 0.25 in. The goal of this exercise is to ascertain if results change dramatically around different temperature and precipitation thresholds.

Results are in the supplementary information in Table S4 and show bus ridership decreases on the coldest (maximum temperature $<$ 40 °F) and hottest (maximum temperature $>$ 90 °F) days by 5.4% ($p < 0.01$) and 1.6% ($p < 0.01$) (resp.) relative to more mild temperatures when daily maximum temperature is between 60 and 80 °F. However, there is no statistically significant effect on days when daily maximum temperatures are between 80 and 90 °F. Effects from days with heavier rainfall (precipitation ≥ 0.5 in.) are similar to results in Table 2. Effects on days when precipitation is between 0.25 and 0.5 in. is also negative and statistically significant, though the size of the effect is smaller compared to days with heavier precipitation.

#### *5.4.3. Impacts within seasons*

Although Eq. (1) includes dummy variables for seasons and year-months, which help account for seasonal trends in bus ridership, to ensure the results are due to extreme weather events, as opposed to seasonal changes, this study also examines impacts within seasons. One issue with this approach is that unusually high temperatures for certain seasons, specifically fall or spring, may still be considered comfortable or mild. For example, Table S5 in the supplementary information shows the 10th and 90th percentiles for daily maximum temperature and precipitation for each season. During the fall and spring (panels B and D resp.), the 90th percentile for daily maximum temperature is 72 and 79 °F, which is less than the threshold of 85 °F used to describe very hot days in Table 2. Consequently, these temperatures are of less interest when considering future impacts from climate change, when very hot days are expected to increase (Hayhoe et al., 2018). As a result, this exercise focuses on the winter and summer seasons only, when very hot and cold days are more likely to occur.

Similar to the main results, the 10th and 90th percentiles for daily maximum temperature and precipitation are used to assess impacts of extreme weather within seasons. However, since extreme weather events are of primary interest, this exercise will only focus on very cold and hot days, characterized as daily maximum temperatures ≤ 10th percentile during the winter and ≥ 90th percentile during the summer (resp.). Impacts from days when precipitation ≥ 90th percentile are also considered during both the winter and summer seasons.

Two separate regressions are run, representing each season using Eq. (1). However the independent variables of interest are either daily maximum temperatures ≤ 10th percentile during the winter or daily maximum temperatures ≥ 90th percentile during the summer. The reference category is more mild temperatures or precipitation during that season. Due to problems around convergence and given the smaller sample size, city-year trends were dropped. However, this should not dramatically change results, since this

study primarily exploits changes in extreme weather events over time.

Results are in Table S6 in the supplementary information and columns 1 and 2 show results for the winter and summer season (resp.). During the winter, in column 1, bus ridership decreases by 4.4% ($p < 0.01$) on very cold days and by 1.6% ($p < 0.01$) on days with high precipitation. In column 2, during the summer, bus ridership reduces by 1.6% ($p < 0.01$) on very hot days, though there is no significant effect on precipitation. The effect of very cold days during the winter and very hot days during the summer on bus ridership is negative, like in Table 2, but the size of the effect is greater.[8]

## 6. Discussion

Given that most LTD buses run every 30 min or hour, which is less frequent compared to other public transit systems in larger cities, bus riders can experience long wait times outdoors. This could make them more sensitive to heat or cold waves or days with heavy precipitation. This study finds decreases in bus ridership on very hot and cold days and on days with heavy rainfall (Table 2). The latter result parallels findings in previous studies showing reduced public transit ridership during poor weather. This study also captures the importance of distinguishing between weekends and weekdays, which could reflect the importance of trip purpose. For example, on very hot days and days with heavy precipitation, results show a smaller reduction in bus ridership on weekends relative to weekdays. However, without more information on other travel modes, it is difficult to determine if this reflects changes in trip generation or mode choice during these extreme weather events.

One neglected component in many studies on transit ridership and weather is explicitly examining the effects of income on this relationship. Due to a rich bus data set, this study explores possible variation in bus ridership between lower- and high-income neighborhoods. Results in Table 3 show the greatest decreases in bus ridership in lower-income census tracts, where average is income is below $50,000, relative to the wealthiest tracts on very hot days. Similarly, on very cold days in areas where average income is between $50,000 and $75,000, bus ridership reductions are also greater compared to the wealthiest neighborhoods. However, on days of heavy precipitation, coefficients on the interaction terms between income and precipitation are positive. This suggests that bus ridership increases in lower-income tracts on these days compared to the wealthiest neighborhoods, which could reflect the fact that many lower-income individuals have less transportation alternatives. Also, a portion of the population who lives in lower-income tracts are near campus and are likely UO students (Fig. 2) who can ride the bus for free, so these changes in bus ridership could also reflect more flexibility across travel modes for this university population. This could partly explain the increase in bus ridership on days with heavy precipitation in lower-income areas. While this study cannot conclude if the changes in bus ridership in lower-income tracts reflect changes in trip generation or mode choice, it suggests bus ridership in lower-income areas is more sensitive on very hot days and days with heavy precipitation relative to their wealthier counterparts. As heat waves and days of heavy precipitation are expected to increase in the Pacific Northwest (Hayhoe et al., 2018), these changes in bus ridership could have meaningful implications for transit agencies.

This study also examines changes in bus ridership around commercial areas and municipal parks during extreme weather events. Results in Table 4 show increases in bus ridership to parks and commercial zones relative to other areas. This result could be due to changes in mode split during extreme weather events, though more information on other travel modes (e.g., biking, walking) is needed to further assess this relationship. These findings suggest that public transit remains an important travel mode for individuals accessing parks and commercial areas, especially on very cold days and days with heavy precipitation.

There may be remaining concerns about using daily maximum temperature or how categories for temperature and precipitation were defined. As a result, robustness checks were performed to assess the sensitivity of results to different specifications. Results in Table S3, which uses daily average temperature, exhibit similar patterns as using maximum temperature in Table 2, where bus ridership decreases on very hot and cold days. The size of the effects on very cold days is similar, though the size of the effect on very hot days is greater using average temperature. The effects of using different temperature and precipitation thresholds are also examined and results in Table S4 show reductions in bus ridership on the hottest and coldest days. They also show reductions in bus ridership mostly being greater with increased precipitation. While the size of the effects in Table S3 and S4 vary slightly from those in Table 2, the pattern is similar, where bus ridership decreases during these extreme weather events. Finally, Table S6 shows impacts during very cold and hot days within seasons, specifically the winter and summer, and the effects are negative, but greater than those in the main results in Table 2. This suggests, that even when comparing unusually cold or hot weather within seasons, effects remain statistically significant and negative. These results collectively show a range of impacts on bus ridership on very hot and cold days and days with heavy precipitation. Findings from these robustness checks do not change the main implications of the results in Table 2, but instead reinforce the importance of extreme weather events on bus ridership.

## 7. Conclusion

This research adds to the literature by observing the relationship between extreme weather and transportation. By leveraging a large micro-level bus data set, this study further examines the importance of income and destination on this relationship. Results

[8] Lack of convergence occurs when looking at impacts during the winter season only. To ensure results do not suffer from omitted variable bias, results in Table S6 column 2 are compared to results that also control for city-year trends. Findings are very similar and show a reduction in bus ridership of 1.5% ($p < 0.01$) on very hot days while the effect on days with unusually high precipitation is also insignificant. This suggests not including city-year trends does not dramatically bias results.

ARTICLE IN PRESS



suggest that extreme weather events, specifically very hot and cold days and days of heavy precipitation, have negative effects on bus ridership, with smaller reductions in bus ridership on weekends. Also, bus ridership in lower-income areas is more sensitive to these extreme weather events, specifically on very hot days and days with heavy precipitation, relative to more wealthy areas. Yet, buses also serve as an important travel mode for trips to parks and commercial zones. Transit agencies, planners, and policymakers should carefully consider how bus ridership will change in the future and prepare as climate change will likely increase the frequency of these events.

Since there is no explicit data on trip type, generation or modal split, it is difficult to make any causal claims. Though, future studies could complement ridership data with information from travel surveys in the same region to address this information gap. Alternatively, a growing number of cities are also using counters to collect data on the number of people who walk or bike on paths that are inaccessible to vehicles. Bus data paired with survey or other bike or pedestrian count data could show the importance of various travel modes during extreme weather events and further inform the importance of trip type and generation on this relationship. Other research could also consider the role of bike shares or transportation network companies, which are becoming more popular alternatives in medium- and large-sized U.S. cities.

## Acknowledgements

I want to thank Jean Stockard for her always helpful feedback and advice and Linmei Amaya for her research support. I am also grateful to Andrew Martin and the other staff at the Lane Transit District who helped me obtain these data. I also want to thank two anonymous referees for their comments and suggestions for improvements on this paper.

## Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2019.03.009.

## References

Arana, P., Cabezudo, S., Peñalba, M., 2014. Influence of weather conditions on transit ridership: a statistical study using data from smartcards. Transport. Res. Part A: Pol. Pract. 59 (January), 1–12. https://doi.org/10.1016/j.tra.2013.10.019.

Böcker, Lars, Dijst, Martin, Prillwitz, Jan, 2013. Impact of everyday weather on individual daily travel behaviours in perspective: a literature review. Transport Rev. 33 (1), 71–91. https://doi.org/10.1080/01441647.2012.747114.

Cools, Mario, Moons, Elke, Creemers, Lieve, Wets, Geert, 2010. Changes in travel behavior in response to weather conditions: do type of weather and trip purpose matter? Transp. Res. Rec. J. Transport. Res. Board 2157 (1), 22–28. https://doi.org/10.3141/2157-03.

Guo, Z., Wilson, N.H.M., Rahbee, A., 2007. Impact of weather on transit ridership in Chicago, Illinois. Transp. Res. Rec.: J. Transport. Res. Board 2034 (1), 3–10.

Hayhoe, K., Wuebbles, D.J., Easterling, D.R., Fahey, D.W., Doherty, S., Kossin, J., Sweet, W., Vose, R., Wehner, M., 2018. Our changing climate. In: Reidmiller, D.R., Avery, C.W., Easterling, D.R., Kunkel, K.E., Lewis, K.L.M., Maycock, T.K., Stewart, B.C. (Eds.), Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II. U.S. Global Change Research Program, Washington, DC, USA, pp. 72–144. doi: https://doi.org/10.7930/NCA4.2018.CH2.

Hofmann, Markus, O'Mahony, Margaret, 2005. The impact of adverse weather conditions on urban bus performance measures – an analysis using ITS technology, p. 7.

Kalkstein, Adam J., Kuby, Michael, Gerrity, Daniel, Clancy, James J., 2009. An analysis of air mass effects on rail ridership in three US cities. J. Transp. Geogr. 17 (3), 198–207. https://doi.org/10.1016/j.jtrangeo.2008.07.003.

Lane Transit District (LTD), 2018a. History > Lane Transit District. < https://www.ltd.org/history/ > (accessed September 5, 2018).

LTD, 2018b. Fare & Pass Pricing > Lane Transit District. < https://www.ltd.org/fare-pass-pricing/ > (accessed September 5, 2018).

May, C., Luce, C., Casola, J., Chang, M., Cuhaciyan, J., Dalton, M., Lowe, S., Morishima, G., Mote, P., Petersen, A., Roesch-McNally, G., York, E., 2018. Northwest. In: Reidmiller, D.R., Avery, C.W., Easterling, D.R., Kunkel, K.E., Lew-is, K.L.M., Maycock, T.K., Stewart, B.C. (Eds.), Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II. U.S. Global Change Research Program, Washington, DC, USA, pp. 1036–1100. doi: https://doi.org/10.7930/NCA4.2018.CH24.

Mote, P., Snover, A.K., Capalbo, S., Eigenbrode, S.D., Glick, P., Littell, J., Raymondi, R., Reeder, S., 2014. Ch. 21: Northwest. Climate Change Impacts in the United States: The Third National Climate Assessment. In: Melillo, J.M., Terese(T.C.), Richmond, Yohe, G.W. https://doi.org/10.7930/j04q7rwx.

Sabir, Muhammad, 2011. Weather and Travel Behaviour. Vrije Universitat Amsterdam.

Sabir, Muhammad, van Ommeren, Jos, Rietveld, Piet, 2013. Weather to travel to the beach. Transport. Res. Part A: Pol. Pract. 58 (December), 79–86. https://doi.org/10.1016/j.tra.2013.10.003.

Scott, Daniel, Jones, Brenda, Konopek, Jasmina, 2007. Implications of climate and environmental change for nature-based tourism in the Canadian rocky mountains: a case study of Waterton lakes national park. Tourism Manage. 28 (2), 570–579. https://doi.org/10.1016/j.tourman.2006.04.020.

Singhal, Abhishek, Kamga, Camille, Yazici, Anil, 2014. Impact of weather on urban transit ridership. Transport. Res. Part A: Pol. Pract. 69 (November), 379–391. https://doi.org/10.1016/j.tra.2014.09.008.

Stover, Victor W., McCormack, Edward D., 2012. The impact of weather on bus ridership in Pierce County, Washington. J. Publ. Transport. 15 (1), 16.

Tang, Lei, Thakuriah, Piyushimita (Vonu), 2012. Ridership effects of real-time bus information system: a case study in the city of Chicago. Transport. Res. Part C: Emerg. Technol. 22 (June), 146–161. https://doi.org/10.1016/j.trc.2012.01.001.

University of Oregon, 2018. UO Facts | Admissions. https://admissions.uoregon.edu/uo-facts (accessed September 5, 2018).

U.S. Census Bureau, 2018. U.S. Census Bureau QuickFacts: Eugene City, Oregon. https://www.census.gov/quickfacts/fact/table/springfieldcityoregon,springfieldcdpvirginia,eugenecityoregon/IPE120216 (accessed August 28, 2018).